Adaptive ECG Compression Scheme with Prior Knowledge Support based on Compressive Sensing

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Abstract—**Mobile electrocardiogram (ECG) monitoring systems have sprung up owing to the considerable interest attracted to wireless body area networks (WBAN). The long-term acquisition process for ECG produces large amount of data, which puts forward high demand on sensor lifetime. Fortunately, compressive sensing (CS) theory has been proved useful in energy saving by compressing signal in certain degree and fulfilling transmission. However, the reconstruction error will increase with fixed compression ratio since users or the sparsity of ECG signal will change during monitoring process. This paper concerns the flexibility and reconstruction quality problem existed in traditional CS-based ECG signal processing. One adaptive ECG compression scheme inspired by closed-loop control theory is proposed, in which the compression ratio can be adjusted according to both real-time reconstruction error and prior knowledge support. Simulation results show that the proposed scheme can improve the compression performance of 10.83% compared with traditional CS-based methods.**

I. INTRODUCTION

Cardiovascular disease takes leading position in threatening human life, it claims responsible for a third of deaths world wide, especially the elderly. According to the national working committee office on aging, China's aging population surpassed 202.43 million by the end of 2013, accounting for 14.9% of the total population. With aging trend in our country becoming more serious, more eyes will undoubtedly be focused to ECG signal. Long term cardiac monitoring process inevitably brought about huge time cost, the mobile healthcare system emerges due to phenomenal growth of WBAN. During mobile ECG monitoring, the ECG can be detected by wearable nodes and transmitted to mobile phone along with remote healthcare center. In this case, doctors can observe persistent information and give diagnosis remotely.

However, high sampling frequency and long-term transmitting process obviously produce large amount of data, which brings energy saving challenge for WBAN. One practical system introduced in [1] indicated that wireless transmission in mobile ECG monitoring process costs half of overall energy consumption. Therefore, it is imperative to do compression work before transmitting collected data. Owing to low frequency and sparse properties of ECG signal, CS-based technique can be used to fulfill ECG signal compression and reconstruction. CS-based methods [2] compress ECG signal to a fewer dimension and transmitted it to the mobile terminal. After wireless transmission, the ECG signal can then be recovered via convex optimization.

There are many researchers focusing on reducing the reconstruction error, such as [3] – [8]. On the one hand, methods in [3] and [4] concentrated on the node side by giving out two modified sparse matrices, which preserved the signal energy and got ready for reconstruction process. [5] and [6], on the other hand, exploited powerful computing performance of the mobile terminal and carried out the bayesian sparse block learning (BSBL) method, which significantly improved reconstruction performance. Works in [7], [8] outperformed previous BSBL method through introducing statistical support at the node side, which made more advantage of the ECG signal.

It is worth noting that all methods described above needed training process to find one fixed compression ratio (CR), reconstruction error will increase if the ECG sparsity experiences severe vibration. What's worse, because the characteristics of ECG signal vary among different users, training process for above methods will inevitably bring a lot of trouble. To solve this issue, an adaptive ECG compression scheme based on compressive sensing is proposed in our paper. In our proposed scheme, the CR parameter is set adjustable according to feedback of real reconstruction error. In this case, the flexibility problem caused by training process will also be solved.

Some error-based adjusting algorithms were proposed in [9] – [11], both linear and nonlinear adjusting methods were introduced. For filter adjusting process, least mean square error algorithms with variable step size (VLMS) was used in [9], [10] to adjust the filter parameter. Unlike this rapid adjusting process, linear formula was exploited in [11] for weather monitoring since the temperature changed once an hour.

Obviously, in an adaptive system, the compatibility between adjusting method and controlled object must be fully considered. As a result, nonlinear adjusting method is used in our system and Directional-VLMS method based on VLMS algorithm is presented.

Besides, due to the positive relationship between the sparsity change and CR change, prior knowledge mined from ECG database will be added as an offline module for sparse prediction. This action brings no extra burden, it will improve the

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performance significantly instead.

Specifically, the main contributions of this paper can be summarized as follows.

- Real-time reconstruction error is generated via introduction of the beacon signal. Compared with previous CS-based ECG signal processing, this move can make reconstruction error applicable for online evaluation without knowing the original ECG signal.
- An adaptive ECG compression scheme based on compressive sensing is presented, it enhances the reconstruction performance compared with traditional CS-based methods.
- Prior knowledge is added as one offline database for sparse prediction, which ensures better reconstruction performance.

The remainder of this paper is arranged as follows. In Section II, we briefly review CS theory and the VLMS algorithm. Then, in Section III, three major parts of our proposed adaptive ECG compression scheme are described. The evaluation indicators and simulation results are given in Section IV. Finally, we draw our conclusion in Section V.

II. Background Research

A. Compressed sensing

For example, we have the original signal x as $n \times 1$ vector, x has sparse representation in DWT basis $(\Psi_i)_{i=1}^{n} \in R^n$, as expressed in (1):

$$x = \Psi\theta = \sum_{i=1}^{n} \Psi_i\theta_i = \sum_{i=1}^{s} \Psi_i\theta_i \tag{1}$$

where $\theta \in n \times 1$ is sparse feature vector of x in Ψ basis and have s non-zero coefficients satisfying $s \ll n$.

If we acquire m measurements via sensing matrix $\Phi \in m \times n$ from original signal x, represented as formula in (2):

$$y = \Phi x = \Phi\Psi\theta = \Theta\theta \tag{2}$$

where y is sampled vector and m satisfies $s < m \ll n$, $\Theta = \Phi\Psi$ is defined as measurement matrix. Φ is defined as random matrices of Gaussian distribution.

We can recover $\tilde{x}$ from $m = cslogN$ measurements according to $\tilde{x} = \Psi\tilde{\theta}$ by solving convex optimization problem in (3):

$$min \parallel \tilde{\theta} \parallel_0 \;\; s.t. \; y = \Phi\Psi\tilde{\theta} \tag{3}$$

where Φ and Ψ obey the restricted isometry property, and c is the over-sampling factor. Greedy algorithms for signal reconstruction such as orthogonal matching pursuit (OMP) is good choice in combining speed with complexity.

B. Variable step size LMS algorithm

The VLMS algorithm was mainly applied in filter parameter adjustment process. It can be expressed as follows:

$$E(k) = d(k) - X^T(k)W(k) \tag{4}$$

$$W(k+1) = W(k) + 2\mu(k)E(k)X(k) \tag{5}$$

where $W(k)$ in (4) is the weighted vector of adaptive filter at time k, $X(k)$ is the input signal vector and $d(k)$ is the desired output, $E(k)$ represents temporal error and $\mu(k)$ is the step length factor. Here, $\mu(k)$ satisfies $0 < \mu < 1/\lambda_{\max}$, $\lambda_{\max}$ is the largest eigenvalue in auto-correlation matrix of the input signal.

One VLMS-based regulating mode is widely used to achieve fast convergence effect in accordance with the precision standard. One variable step size strategy can be expressed as the following formula:

$$\mu(k) = \beta(1 - \exp(-\alpha \mid E(k) \mid^2)) \tag{6}$$

where α controls the function shape and β controls the scope, they satisfy $\alpha > 0$, $\beta > 0$.

III. Proposed Scheme

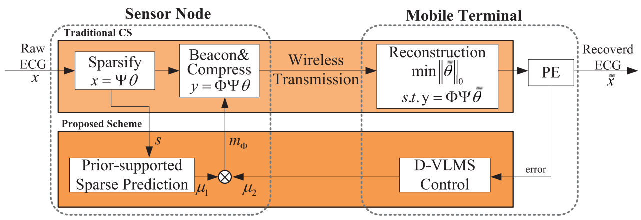

Fig. 1: CS-based Adaptive ECG Compression Scheme.

The CS-based adaptive ECG compression we propose is marked in Fig.1, which contains the sensor node and the mobile terminal. Traditional CS-based ECG sinal processing is illustrated in upper part of the Fig.1, raw ECG data x can be compressed to y after sparse map at the sensor node. After transmission process, compressed data is recovered at the mobile terminal via OMP reconstruction. According to auto-control theory, we set compressed dimension m dynamic and create a control system by adding three functional parts: PE, D-VLMS control and prior supported sparse prediction to traditional CS-based ECG processing methods.

A. PE: percentage root-mean-square difference (PRD) estimation

In control system, the controller makes sense by comparing output of controlled object with the reference value and then uses their D-value to drive actuator. Inspired by this idea, we draw evaluation of real-time monitoring quality by comparing real-time reconstruction error with observing demand in standard. The indicator PRD is used to measure difference between the original and reconstructed signal. However, real-time PRD can't be generated since original ECG signal value is unknown in monitoring process, existing research just utilizes this indicator for offline evaluation. For evaluating temporary monitoring quality, we randomly choose a tiny part from original signal as beacon signal in each frame and record their position information along with value. Compressed signal is transmitted to the mobile terminal together with beacon information, then real-time PRD can be calculated via formula expressed in (7):

$$PRD_l = \sqrt{\frac{\sum_{i=1}^{l}(x_i - \tilde{x}_i)^2}{\sum_{i=1}^{l} x_i^2}} \times 100\% \tag{7}$$

where x_i is the beacon signal, $\tilde{x}_i$ is reconstructed signal which lists in the same position as beacon signal, l is length of beacon signal, here we choose $l = 15$.

This action is effective because when n is not too big, PRD_l is similar to global PRD. Proofs of our estimation and determination of length l are given in the next section.

Through this method, we can obtain real-time PRD, which will be used to calculate the reference error in comparison with reconstructing demand in standard. As given in [13], if PRD_k reaches 9% or below at time k, current CR_k or compressed dimension m can be considered as qualified to achieve good reconstruction performance, so we treat $e(k) = PRD_k - 9\%$ as controller to drive adjusting operation of dimension m.

B. D-VLMS control

After determining real-time $e(k)$ at time k, we need adjusting method as actuator for better ECG reconstruction. As given in Section II, the VLMS algorithm has been proved useful in calculating optimal step length as per time-variant error value $e(k)$. However, the VLMS algorithm can't be exploited directly here since step direction is uncertain without considering the symbol of $e(k)$. Similar to previous works, compressed dimension m has a relatively negative relationship with reconstruction error $e(k)$. That is to say, m can be increased in order to enhance observing quality if $e(k) > 0$, and it can be decreased for saving wireless transmission in return. As a result, we create $sign(e(k))$ as a threshold function here for tagging direction of adjustment, it is expressed in (8):

$$sign\,(e(k)) = \begin{cases} 1 & if\ e(k) > 0 \\ -1 & if\ e(k) \leqslant 0 \end{cases} \tag{8}$$

By adding directional guide to the VLMS algorithm, D-VLMS control can be achieved. To be specific, during the D-VLMS adjusting process, directional broad step length is used when reconstruction error is great and small step size is used when the error gets smaller, the formula for step size $\mu_1(k)$ can be seen in (9):

$$\mu_1(k) = round(\beta(1 - \exp(-\alpha \mid e(k) \mid^2))) \times sign(e(k)) \tag{9}$$

After determining $u_1(k)$ for current $e(k)$, it can be used to change compression parameter m at time $k+1$, as described in (10). The parameter L_{TH_1} is introduced to avoid overshoot problem, which exists when $u_1(k)$ is huge and $m(k)$ is undergoing severe shock. Besides that, $m(k)$ is set as stable if $u_1(k) < L_{TH_2}$, thus achieving the effect of convergence.

$$m\,(k+1) = \begin{cases} m(k) + L_{TH_1} & \text{if } u_1(k) > L_{TH_1} \\ m(k) & \text{if } u_1(k) < L_{TH_2} \\ m(k) + u_1(k) & \text{else} \end{cases} \tag{10}$$

The value of time period k is $1, 2, 3, \cdots$ and k satisfies $k \geqslant 1$, $m(k)$ represents the row value of sensing matrix Φ, we should initialize $m(1)$ for the first compression and transmitting process.

C. Prior-supported sparse prediction

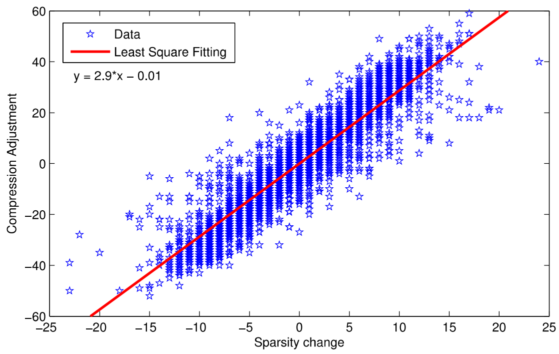

Fig. 2: Sparsity change versus compression adjustment in accurate reconstruction.

Due to time-lag effect, closed-loop control may not fully undertake adjusting task since signal has diversity in each frame, along with sparse change. Therefore, we add prior supported sparse prediction as feed-forward loop and make compensation for D-VLMS control described above.

Since the sparsity s of signal varies for each time period, huge shock of s will result in bad reconstruction effect. Feedback control may not reach the requirements of accurate reconstruction, we attempt to add additional regulation mode according to signal diversity. We select 409600 data from MIT-BIH Arrhythmia database, then complete CS-based process in simulation on condition that the reconstruction error is within acceptable level (less than 9%), we get two 3193×1 dimensional vectors representing ECG sparsity $s(1{:}\ 3193)$ versus compressed dimension $m(1{:}\ 3193)$ from time 1 to $k+1$. After calculation of first order difference, which can be expressed as follows:

$$\triangle s(k+1) = s(k+1) - s(k) \tag{11}$$

$$\triangle m(k+1) = m(k+1) - m(k) \tag{12}$$

we can generate two 3192×1 dimensional vectors representing sparse change $\triangle s(k+1)$ versus dimensional change for compression $\triangle m(k+1)$ in adjacent time periods as shown in Fig.2.

Obviously, positive relationship can be found between vertical and horizontal axis, we then construct a model to calculate corresponding compression adjustment after measuring the change of ECG sparsity. In order to prevent over fitting, the least square fitting of first order is adopted and then one linear model is concluded to characterize these two variables in (13):

$$\mu_2(k+1) = round(K \times \triangle s(k+1)) \tag{13}$$

where K refers to the slope of linear mapping function. $\triangle s(k+1)$ is the sparse change of ECG signal, it can be calculated by subtracting sparsity in adjacent time periods from k to $k+1$. As a result, $\mu_2(k+1)$ is the feed-forward prediction for compression adjustment.

By adding this sparse prediction to feedback-control result of last time k, we can obtain gross compression $m(k+1)$ for time $k+1$, thus ensuring comprehensive optimization effect.

IV. Simulation Results

In this section, evaluation indicators for mobile ECG monitoring system and simulation results are provided to illustrate the effectiveness of the proposed scheme. The database is extracted from the recognized MIT - BIH Arrhythmia database. It has 48 ambulatory ECG recordings with sampling frequency of 360 Hz. We take 12800 data in total from group 108 as testing data, complete compression and reconstruction process from time step 1 to 100 with frame length $n = 128$. And also, we do the same experiment for 50 times and calculate the average value of experimental results.

A. Evaluation indicators

Generally, there are two evaluation indicators for mobile ECG monitoring: the compression ratio (CR) and PRD. CR is the ratio of bits number for original signal and compressed sequence in each frame, it can be expressed by the following formula in (14) and (15) :

$$CR = \frac{B_N}{B_M + B_{beacon}} \tag{14}$$

$$PRD = \frac{\|x_i - \tilde{x}_i\|_2}{\|x_i\|_2} \times 100\% \tag{15}$$

where B_N and B_{beacon} represent the bit number of original signal and beacon information, B_M represents the bit number of compressed signal and n stands for total length in each frame.

B. Error estimation performance

As introduced in Section III, we randomly choose a tiny part from original signal in length l and record their position information and value. After reconstruction process at the mobile terminal, PRD_l can be calculated as replacement for PRD, which marks the monitoring quality. For determining length l of the beacon signal, we initialize one small value of l, then iteratively increase it until (16) can be satisfied.

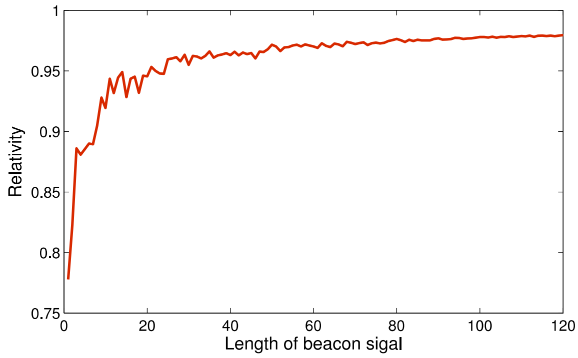

Fig. 3: Relativity between PRD and PRD_l. .

$$R = 1 - \sqrt{\frac{(PRD - PRD_l)^2}{PRD^2}} > \epsilon \tag{16}$$

where ϵ is the relativity threshold and R stands for the relativity of PRD and PRD_l. We select first 128 data from record 108 as an example and iteratively complete R calculation with increasing l. As shown in Fig.3, R will soon become stable after first few big steps, if we take 95% as the standard for similarity, then only 15-20 beacon signals will be sampled for error extraction.

Through this method we can obtain real-time PRD, which will act as one reference for compression adjustment in part of our proposed strategy.

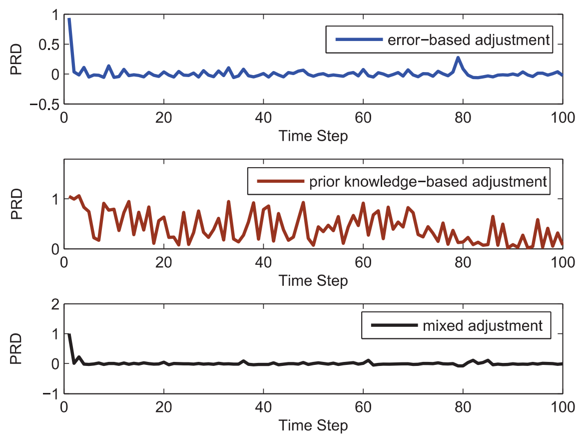

Fig. 4: PRD value for 3 control methods.

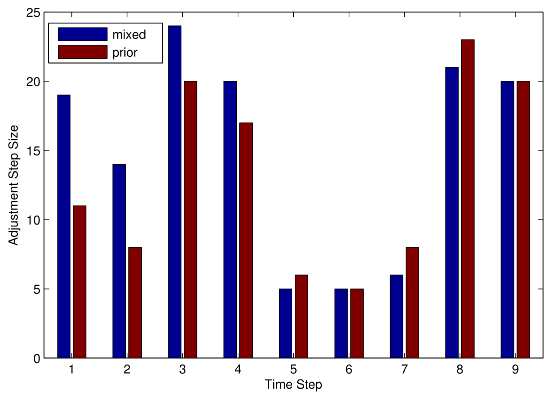

Fig. 5: Bar chart for prior-based and mixed adjustment.

TABLE I: Results of CR value

Dataset	CR in Our scheme	CR in Traditional CS
101	4.02	3.56
102	3.85	3.42
103	4.14	3.78
104	3.98	3.52
105	3.72	3.32
106	4.20	3.73
107	4.08	3.63
108	3.86	3.43
Avg	3.98	3.55

C. Control performance

In Fig.4, PRD_l value is given from time step 1 to 100 in case of feedback-only control, prior knowledge-only adjustment and our proposed comprehensive scheme respectively. It is obvious that our method can automatically adjust compression parameter according to both signal diversity and real-time reconstruction error, it also guarantees observing quality for remote health-care center.

It is worth noting that the gap between total compression adjustment and prior knowledge-based adjustment will soon vanish in a short period of time. That is to say prior-based adjustment will play a dominant role after convergence, which is shown in Fig.5.

Since the CR value is adjusted according to real-time PRD value, a large initial value for CR is set in the purpose of transmission saving. We choose additional data set from MIT-BIH database in testing the proposed scheme, corresponding CR value from time step 1 to 10 is given in the following table, which also gives a comparison with CR value of traditional CS-based methods. It is worth mentioning that when the user switches, our proposed adaptive ECG compression method can improve the transmission performance of 10.83% than traditional CS-based methods.

V. CONCLUSION

This paper proposes a novel scheme for CS-based ECG compression. Considering the flexibility and reconstruction quality in body area network, an adaptive ECG compression scheme is presented by adding three major functional parts to traditional CS-based methods. Combined with experimental results, our proposed system is proved to be efficient and practical.

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